Climate Model Performance Metrics

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Presentation Outline:

- **Background on model metrics**
- **Exploratory work with simulations from the Coupled Model Intercomparison Project (CMIP)**
  - **Mean climate**
  - **Variability**
- **Cloud-radiative effects**
- **Where do we go from here**
- **The continuing need for new observations**

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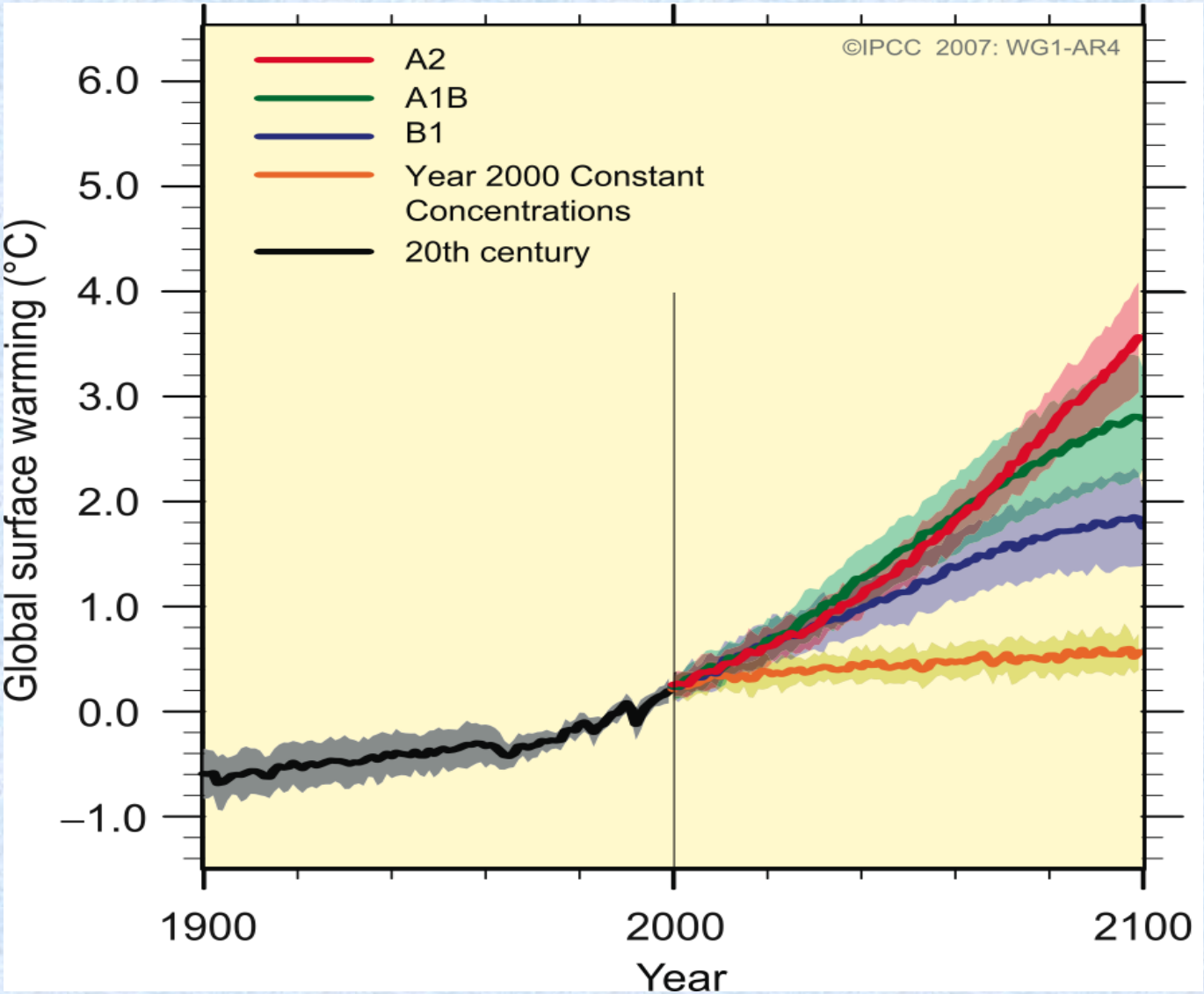
Motivating Questions:

- **Are climate models improving? If so, how rapidly?**
- **Are some models more realistic than others?**
- **How does skill in simulating observed (past and present) climate relate to credibility of model projections?**
- **Can we justify weighting models, based on metrics of skill, to optimize use of multi-model ensembles in making projections of climate change?**

UCRL-ABS-233830

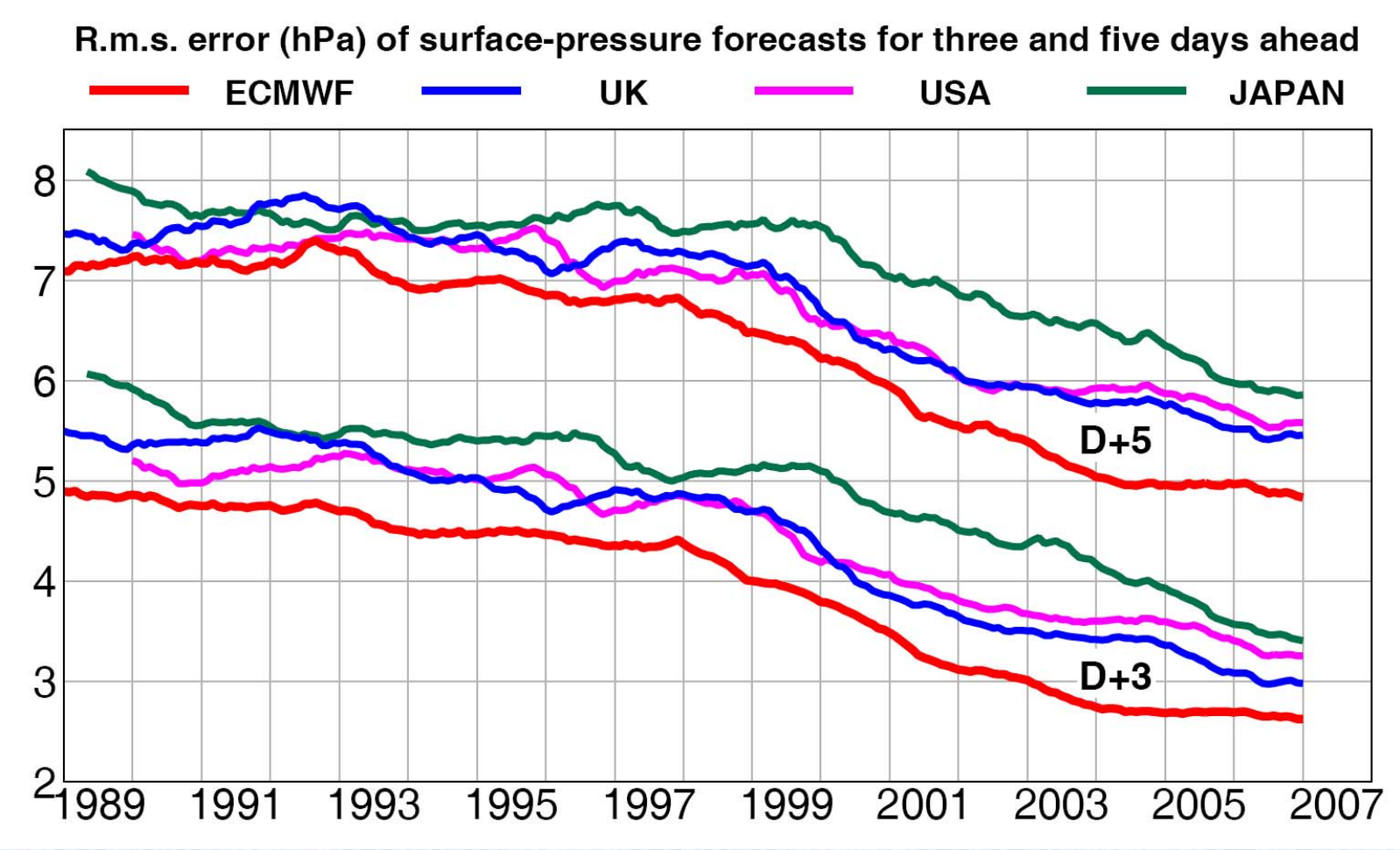
Figure from IPCC AR4 "Summary for Policy Makers"

Global average surface warming as simulated by climate models for different scenarios



Monitoring evolution of model performance: Example from Numerical Weather Prediction

- WGNE routinely reviews still of daily forecasts
- Improvements and deficiencies in the systems identified



Courtesy M.Miller, ECMWF

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What do we mean by “metrics”?

- **“Metrics”, as used here, are scalar quantities that objectively measure the quality of a model simulation, e.g.,**
  - → **Skill in simulating things we have observed (“performance metrics”)**
  - → **Model reliability for applications (e.g., “projection reliability metrics”)**
    - **How accurate are model projections of climate change?**
    - **Extremely valuable… and… extremely difficult**
- **Quantify errors, but usually *not* designed to diagnose reasons for model errors**

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Some recent work on climate model "performance metrics"

- Gleckler, P., K. Taylor, and C. Doutriaux, 2008:
  Performance metrics for climate models, JGR, *in press*

- Pincus, R., Batstone, C., Hoffman, R., K. Taylor, and P. Gleckler, 2008:
  Evaluating the present-day simulation of clouds, precipitation and radiation in climate models, JGR, accepted

- Reichler, T., Kim J., 2008:
  How well do coupled models simulate today's climate?, BAMS, *in press*

- Williams, K., and M. Webb, 2008:
  A quantitative climate performance assessment of cloud regimes in GCMs, Climate Dynamics, *submitted*

What opportunities are there to evaluate models and build confidence in model physics & dynamics?

- **Model's externally "forced" responses on a range of time-scales:**
  - → **Diurnal cycle**
  - → **Annual cycle**
  - → **Volcanic eruptions, changes in solar irradiance, …**
- **Model's "unforced" behavior (weather, MJO, ENSO, NAO, PDO …)**
- **Evaluate model representation of individual processes and co-variability relationships**
- **Test model ability to solve the "initial value" problem**

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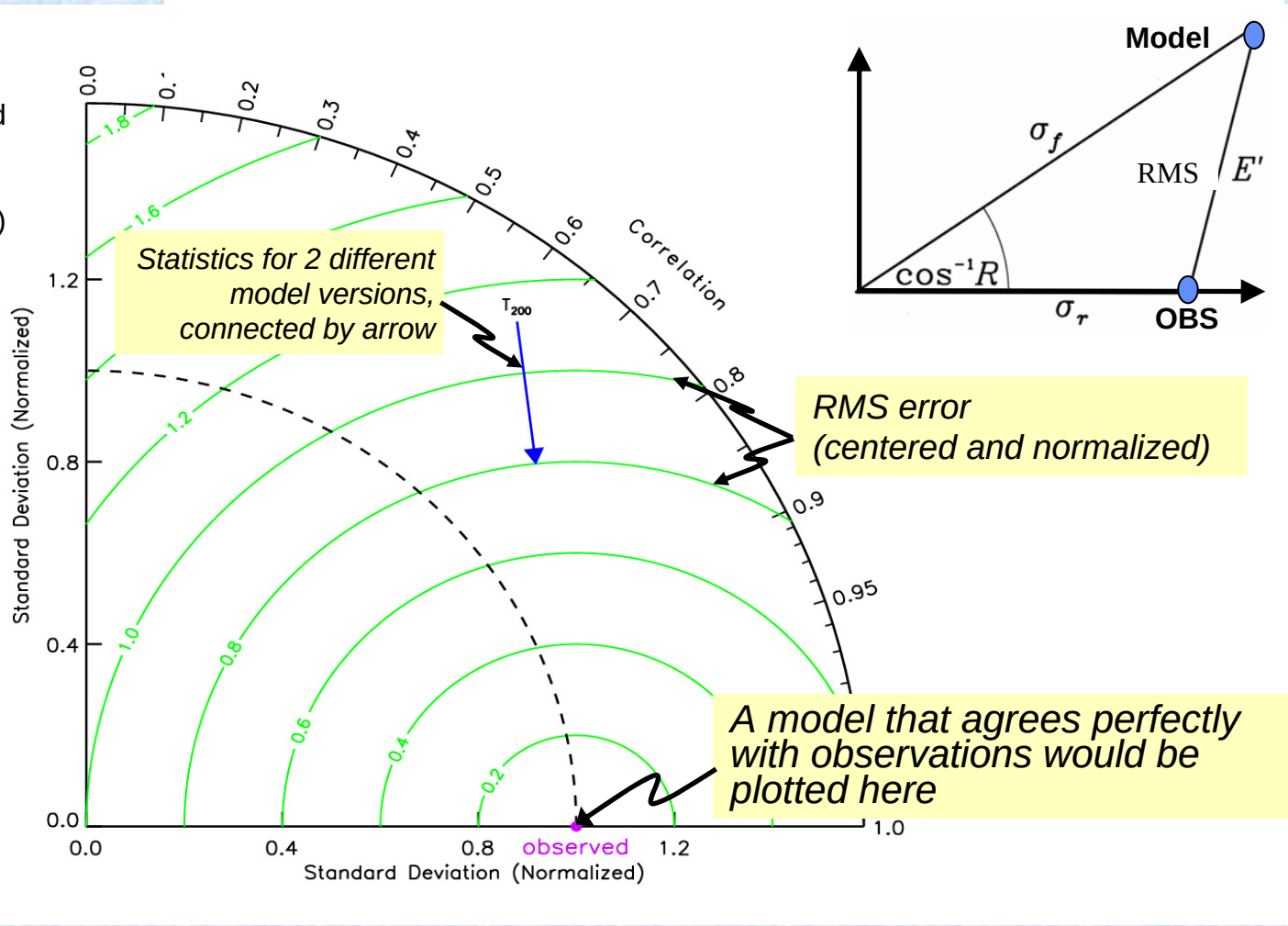
Three statistics characterizing agreement between simulated and observed fields can be shown: Taylor Diagram

(Note: Can be extended to include negative correlations)



Taylor, *J. Geophys. Res.* (2001)

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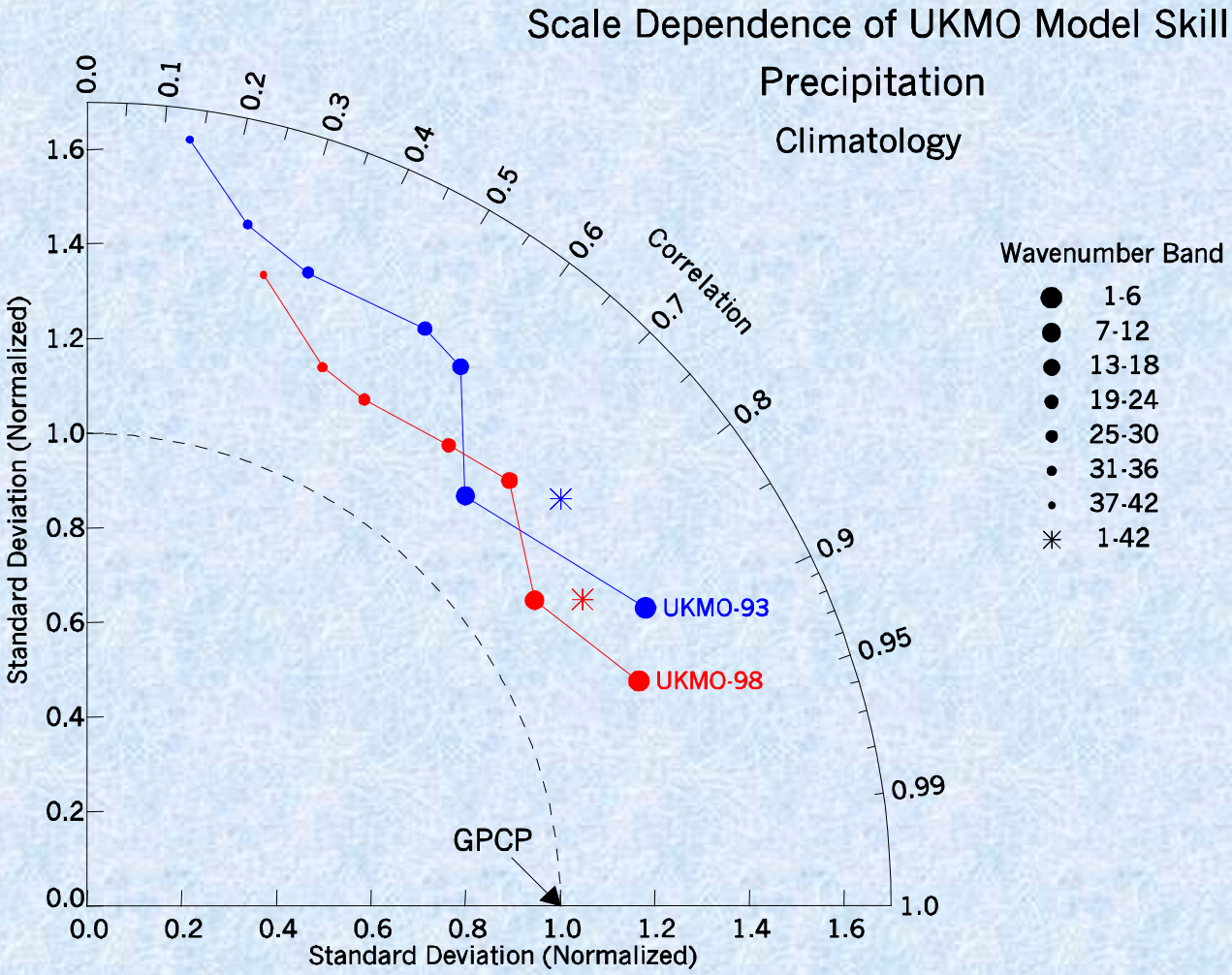
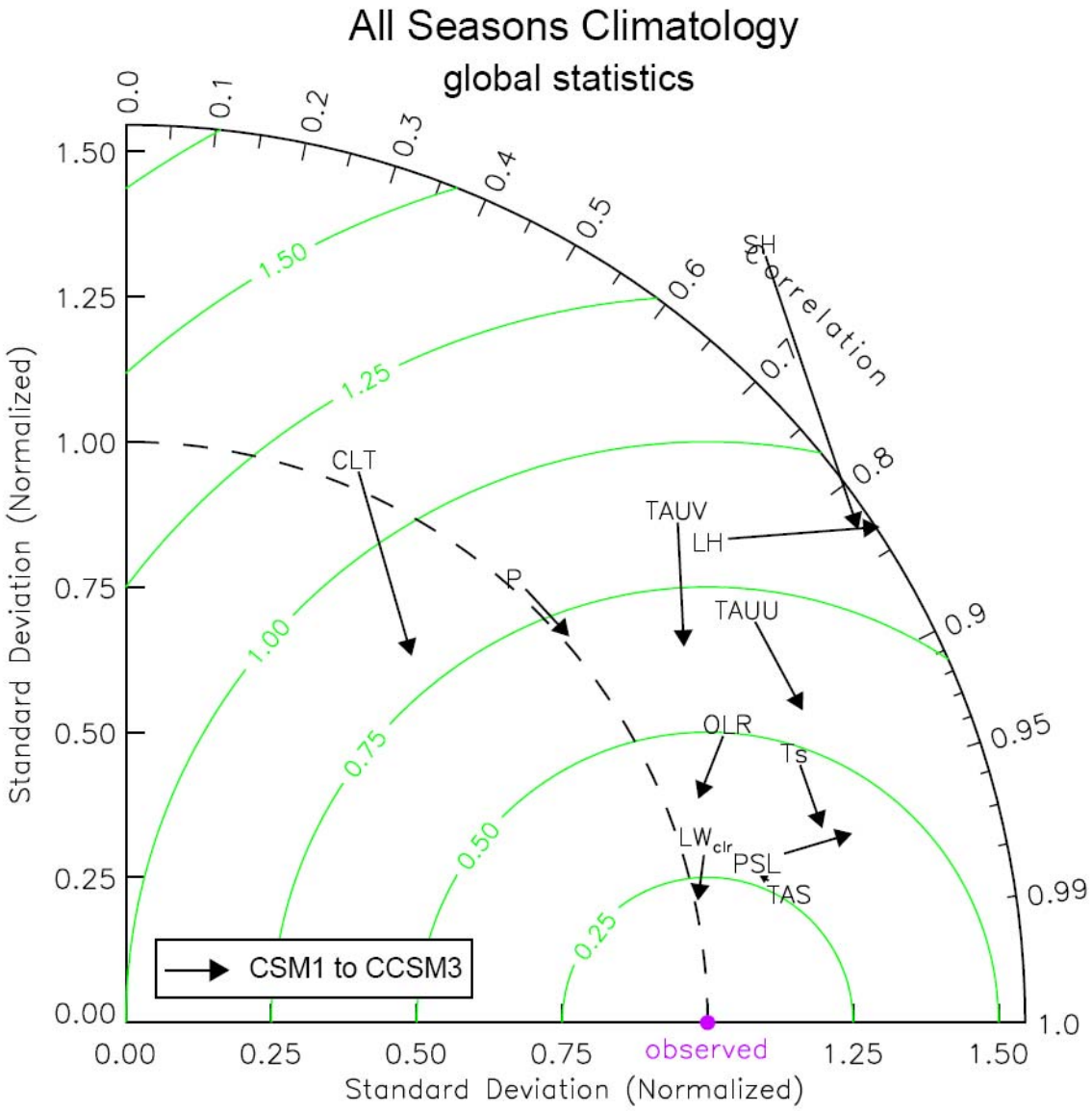
The larger the scale the better the model skill



Tracking model performance in the development process



Providing feedback to NCAR on newer model versions

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The CMIP3 multi-model dataset

- 2003-2004: In anticipation of the IPCC AR4, PCMDI assisted the World Climate Research Programme's Working Group on Coupled Modelling (WGCM) in the design and coordination a new suite of experiments
- 2004-2005: Modeling groups performed simulations and submitted standardized output to PCMDI for dissemination
- 2005-present: Early publications form the basis of model analysis in the IPCC AR4. To date, over 250 publications based on CMIP3

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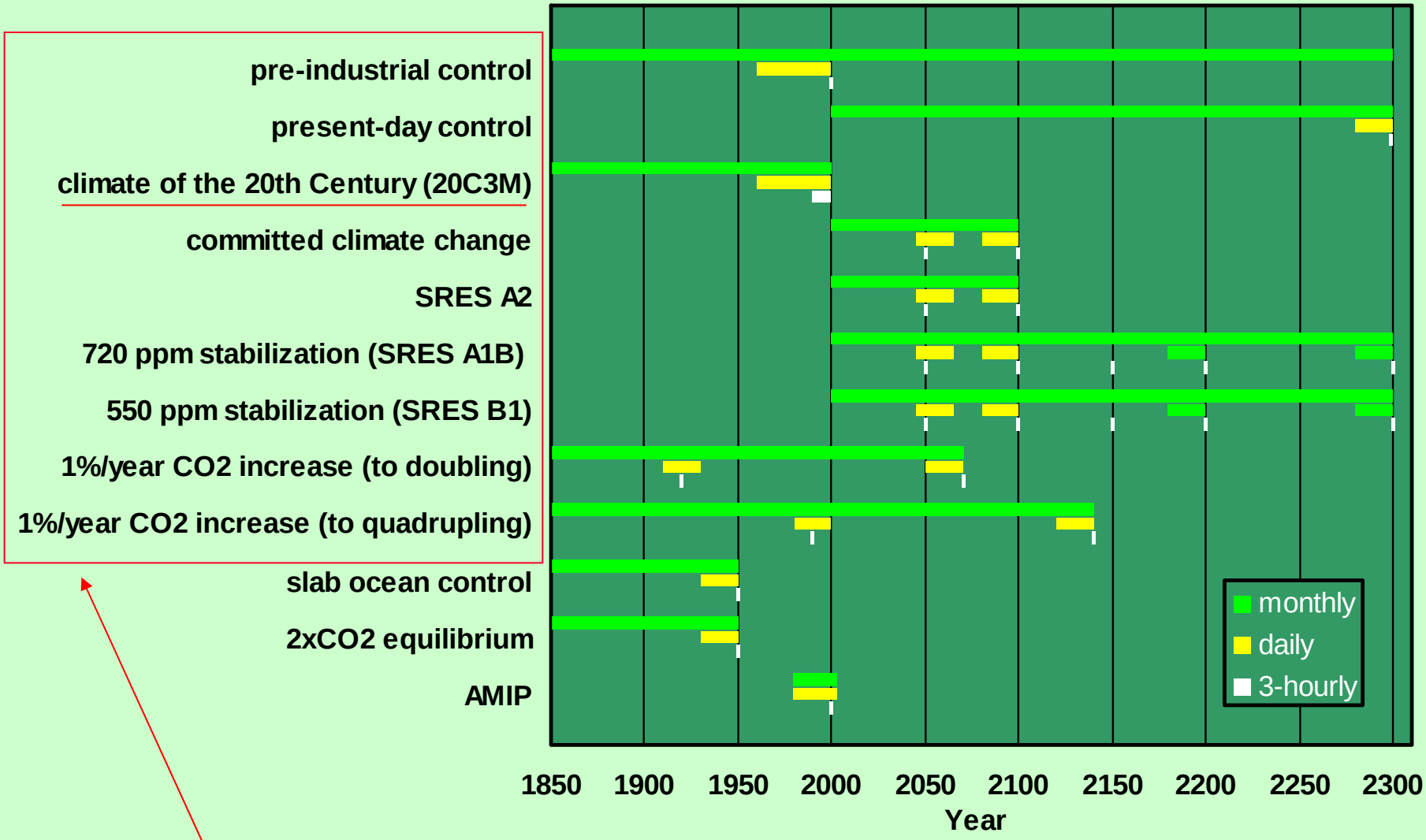
Sampling by experiment



Fully coupled OAGCM runs

External forcings applied in the "20th Century" simulations

	Model	G	O	SD	SI	BC	OC	MD	SS	LU	SO	V
1	CCCma-CGCM3.1(T47)											
2	CCSM3											
3	CNRM-CM3											
4	CSIRO-Mk3.0											
5	ECHAM5/MPI-OM											
6	FGOALS-g1.0											
7	GFDL-CM2.0											
8	GFDL-CM2.1											
9	GISS-AOM											
10	GISS-EH											
11	GISS-ER											
12	INM-CM3.0											
13	IPSL-CM4											
14	MIROC3.2(medres)											
15	MIROC3.2(hires)											
16	MRI-CGCM2.3.2											
17	PCM											
18	UKMO-HadCM3											
19	UKMO-HadGEM1											

Well-mixed GHGs | Ozone | Sulfate (direct) | Sulfate (indirect) | Black carbon | Organic carbon

Mineral dust | Sea salt | Land use | Solar irradiance | Volcanic aerosols

Reference data sets

Fields	Reference / alternate
Zonal and meridional wind Temperature,Geopotential, 2m air temperature, 2m humidity and 10 winds	ERA40 / NCEP-NCAR reanalysis
TOA Radiative Fluxes: Outgoing Longwave (OLR), clear-sky fluxes	ERBE /CERES
Precipitable water	RSS / NVAP
Precipitation	CMAP / Xie-Arkin
Specific Humidity	AIRS/ ERA40
Total cloud cover	ISCCP-D2 / ISCCP-C2
Sea surface temperature (SST)	HadiSST / ERSST
Wind stress (ocean)	ERA40 / NCEP-NCAR
Ocean surface fluxes: latent and sensible (pattern only)	SOC / ERA40

Annual cycle performance metrics

- **Evaluate the climatology (1980-1999) of CMIP3 20th Century simulations with:**
  - → **~ 20 well-observed atmospheric variables**
  - → **Space-scale: global domain, coarse model grid (T42: 128x64)**
  - → **Time-scale: annual cycle**
- **Error statistics calculated by summing over all grid cells and the 12 climatological months**

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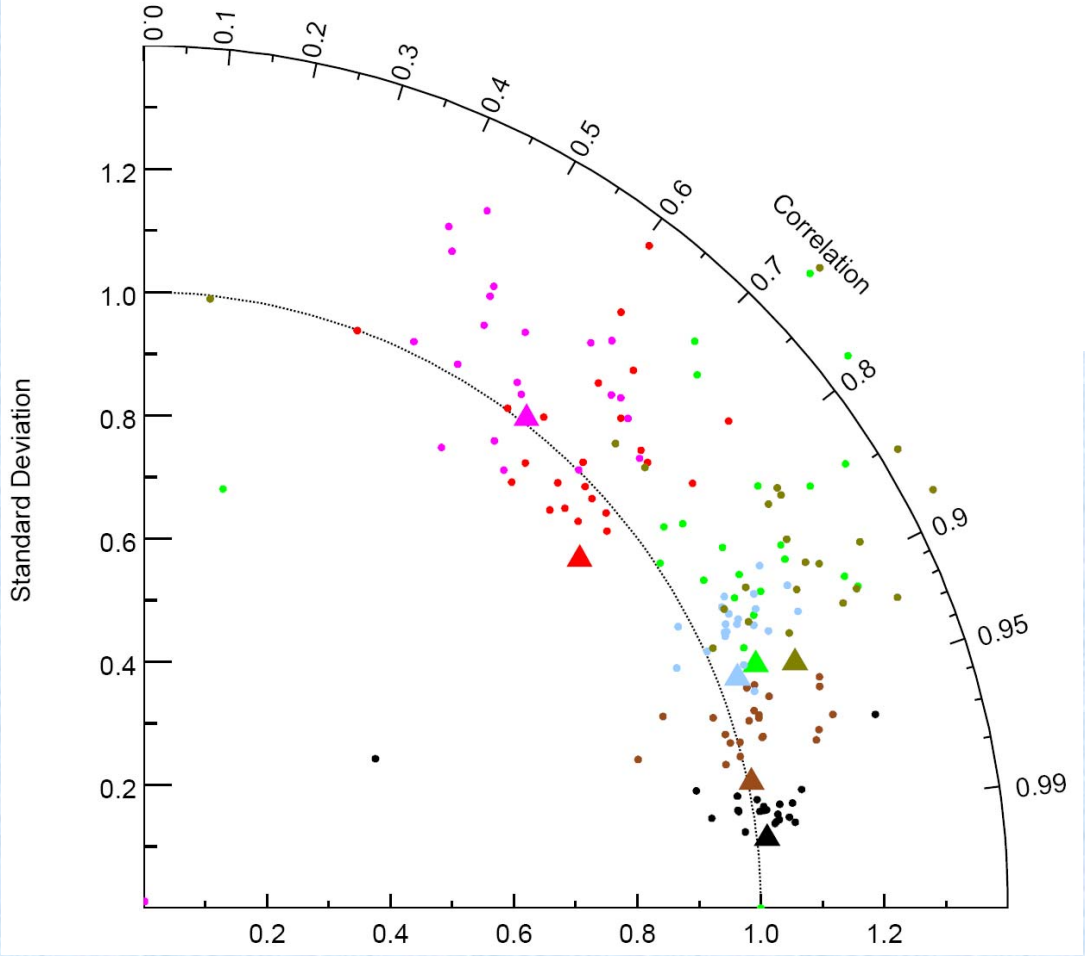
Taylor diagram for CMIP3 annual cycle global climatology (1980-1999)



Sea Level Pressure: ERA40 reference
Total precipitation rate: CMAP reference
Total Cloud Cover: ISCCP reference
LW radiation TOA (OLR): CERES reference
Reflected TOA Shortwave: ERBE reference
Air Temperature (850 hPa): ERA40 reference
Zonal Wind (850 hPa): ERA40 reference

- Variable dependent skill
- Multi-model mean "superiority"

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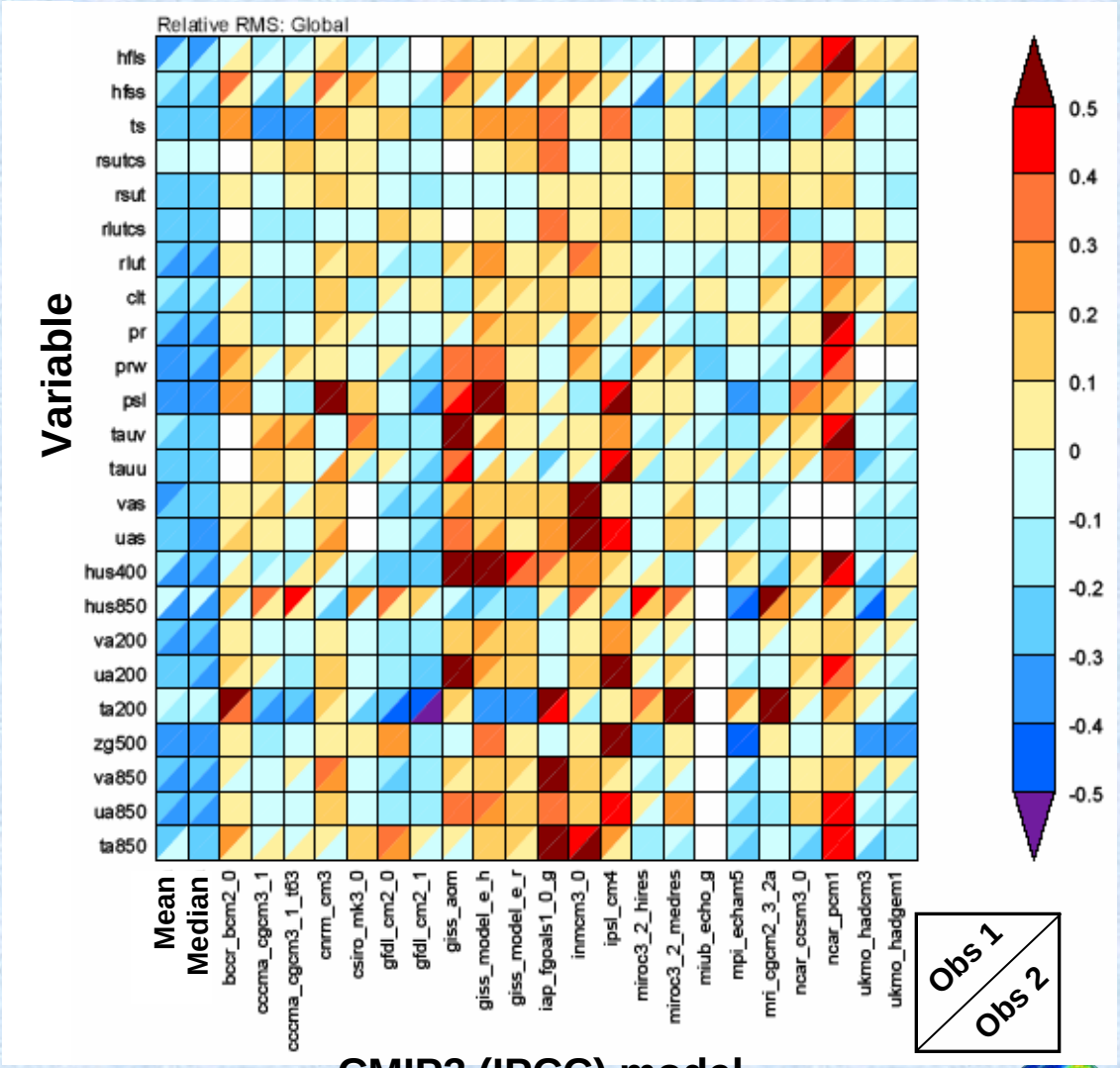
Annual cycle of global fields: Assessment of the relative skill (S) of individual CMIP3 models.

E_{vm} = RMS error in simulating the spatial pattern of the climatological annual cycle of variable v by model m

$$S_{vm} = \frac{E_{vm} - \hat{E}_v}{\hat{E}_v}$$

where $\hat{E}_v$ is the median of the individual error measures, E_{vm}



Gleckler, Taylor, & Doutriaux, 2008, *JGR, in press*

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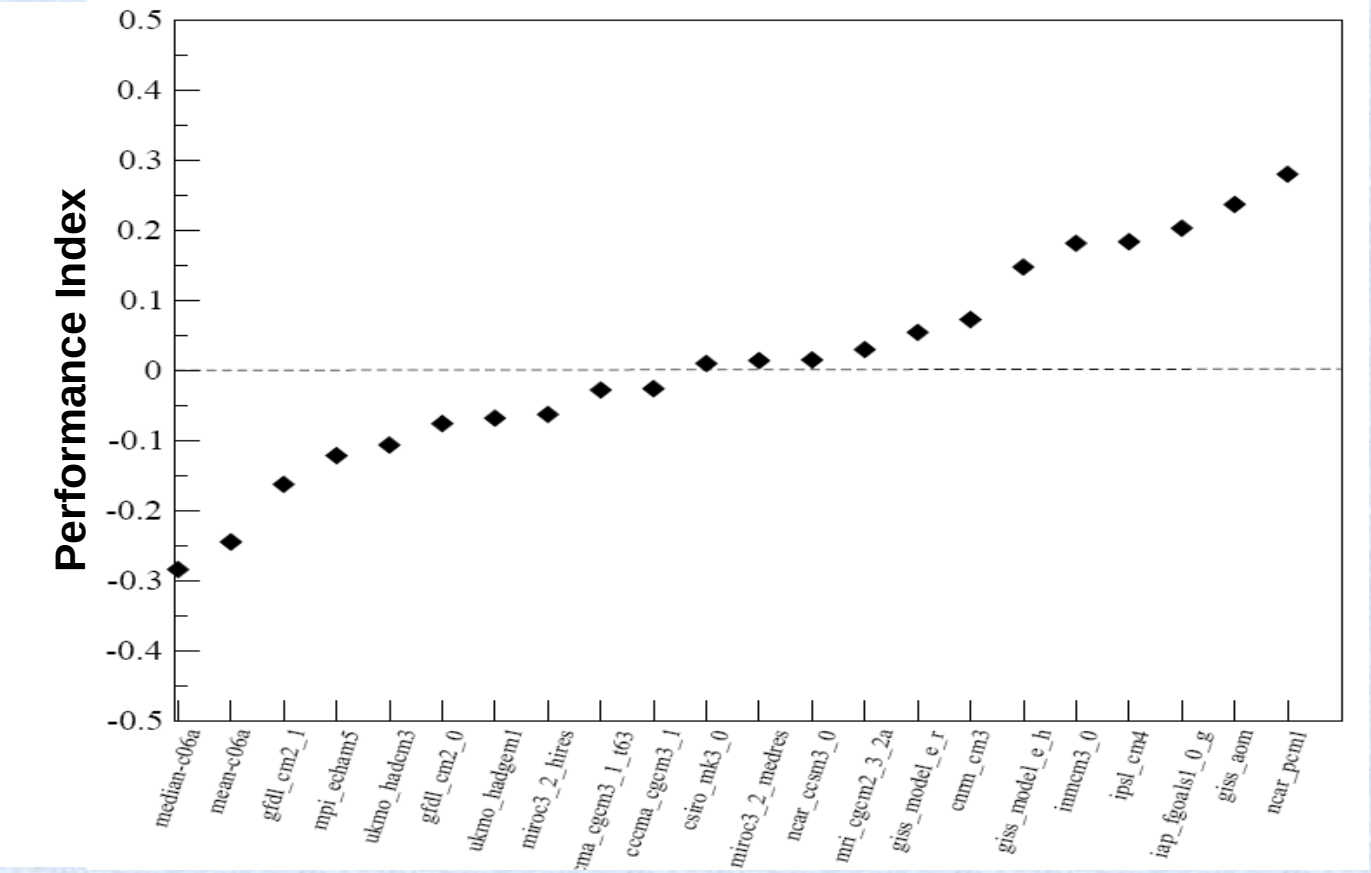
Exploring the value and limitations of a single "performance index".

- **From performance portrait recall:** $$S_{vm} = \frac{E_{vm} - \hat{E}_v}{\hat{E}_v}$$
- **Let the "performance index" be the mean of S_{vm} over all the variables.**



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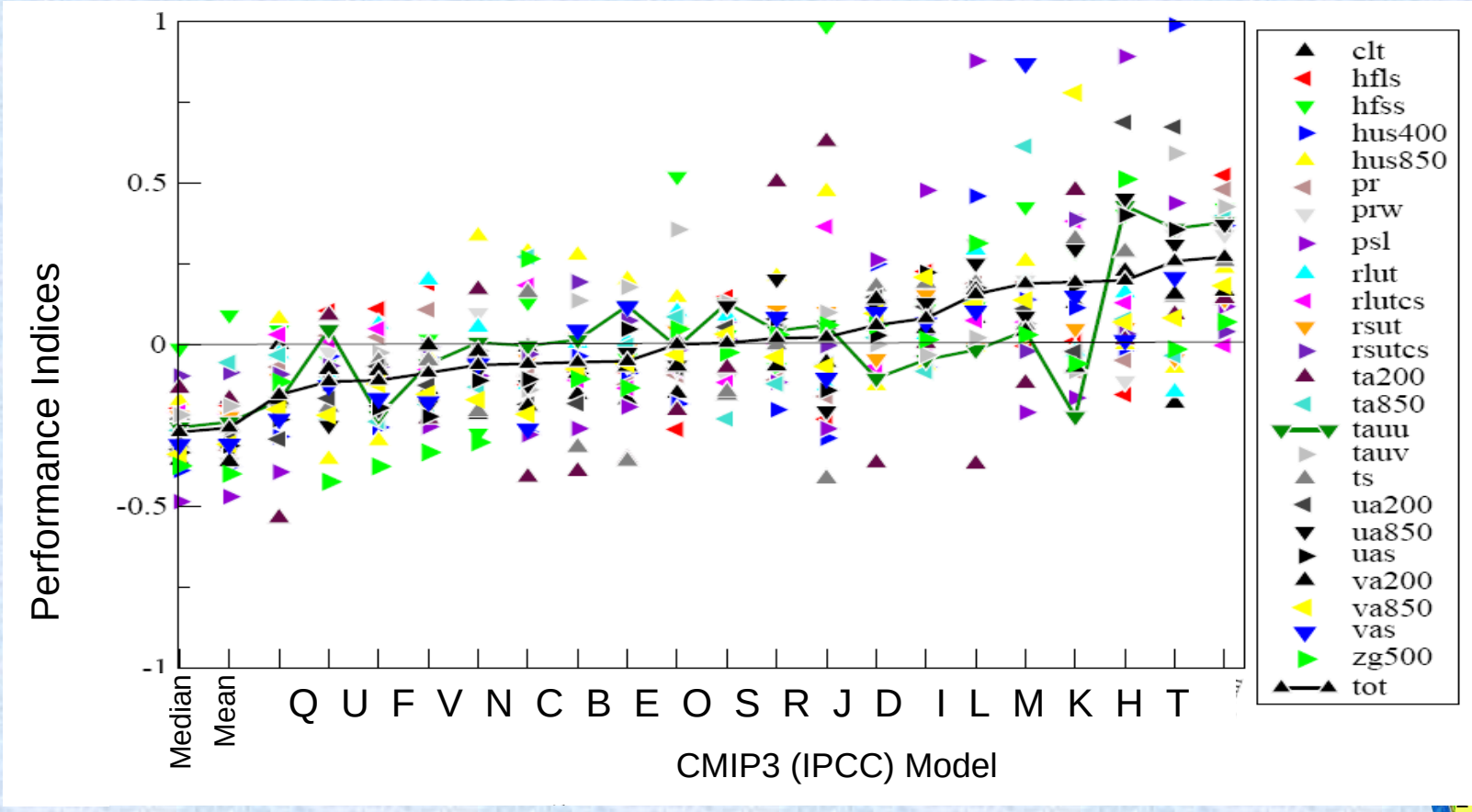
Is the “performance index” meaningful/useful?

- **Little correlation between simulation of individual fields and an index.**
- **Ranking of models will depend on which metrics are included in index.**



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Premature to unduly emphasize a single performance index

- **Fails to capture the complex error structure of models**
- **Depends on a number of factors (variable, region, time-scale, etc.)**
- **Invites simplistic interpretations of the relative value of specific models - the emphasis should be towards correct representation of the physics.**
- **Optimal weighting of different metrics contributing to a performance index likely depends on the application**

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Do we know what is most important for reliable projections?

No, but …

- Cloud-radiative effects are an obvious place to start
- Cloud-Feedback Model Intercomparison Project (CFMIP):

Objective of CFMIP-2 is to make an improved assessment of:

→ climate change cloud feedbacks by making progress in the
(1) evaluation of clouds simulated by climate models and the
(2) understanding of cloud-climate feedback processes.

→ From a practical standpoint – participating modeling groups provide "ISCCP simulator" output from standard experiments

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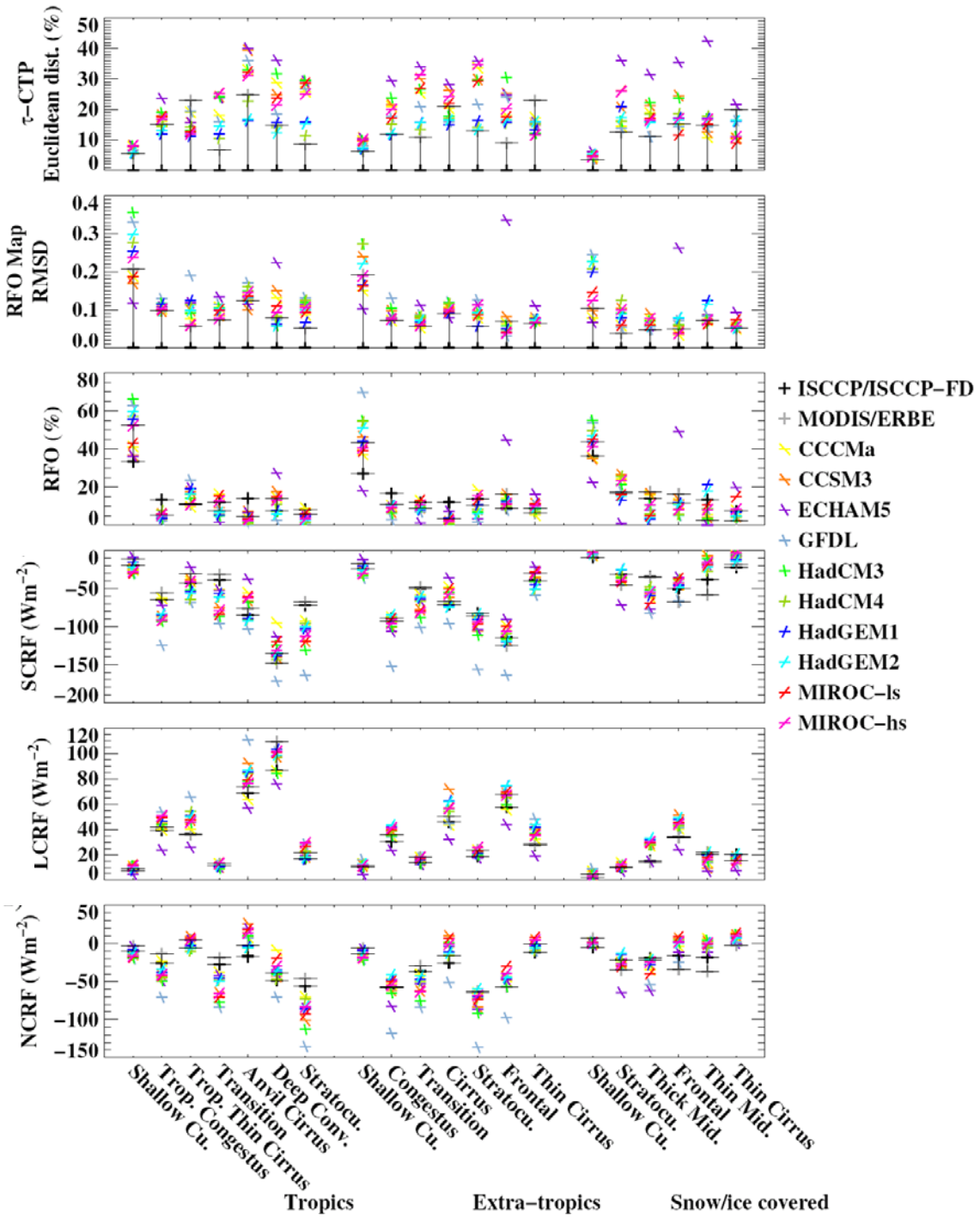

Williams and Webb, 2008

(Climate Dynamics, submitted)

- CFMIP slab ocean exps
- Joint τ-CTP cloud amount histograms
- 5 yrs of daily mean ISCCP simulator and CRF
- Similar from MODIS

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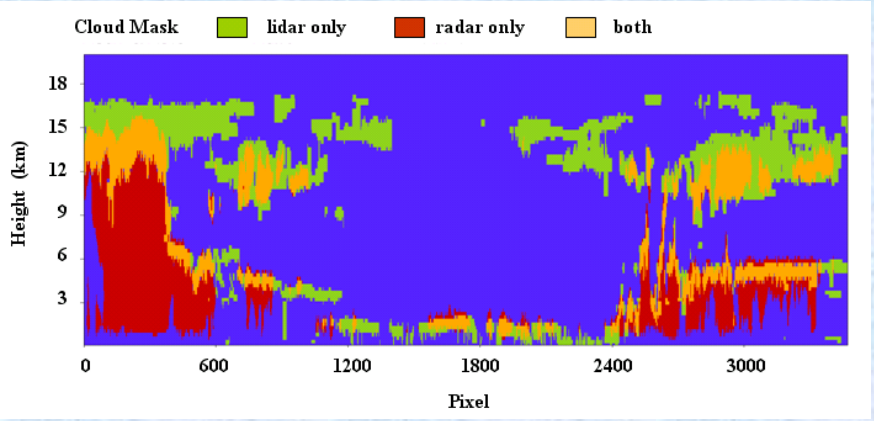
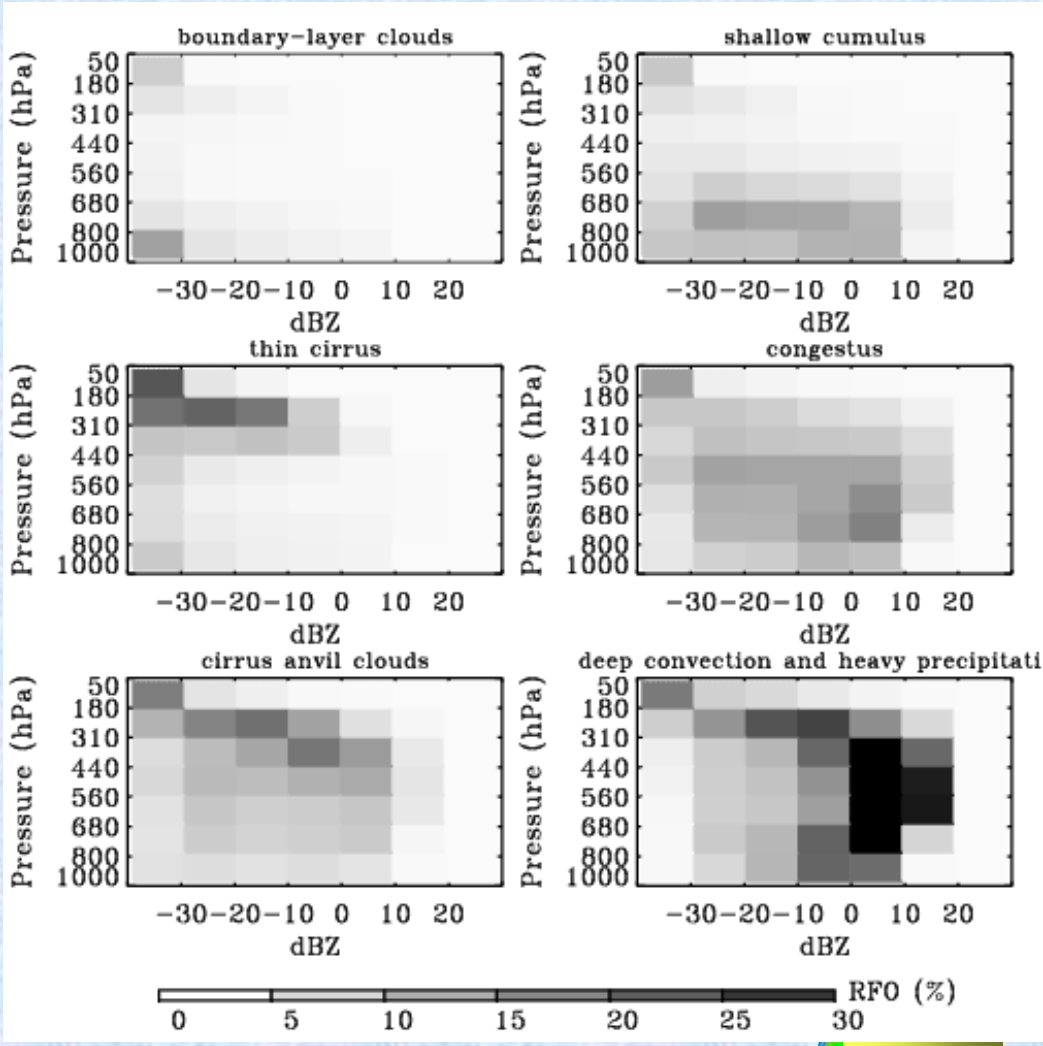
Define principal clusters of cloud regimes from observations (courtesy Yuying Zhang and Steve Klein of PCMDI)



- Combined CloudSat and CALIPSO data provide most accurate description on vertical structure of cloud fields (Mace et al. 2007&2008)
- Patterns of cloud clusters defined using combined dataset (Zhang et al. 2007)



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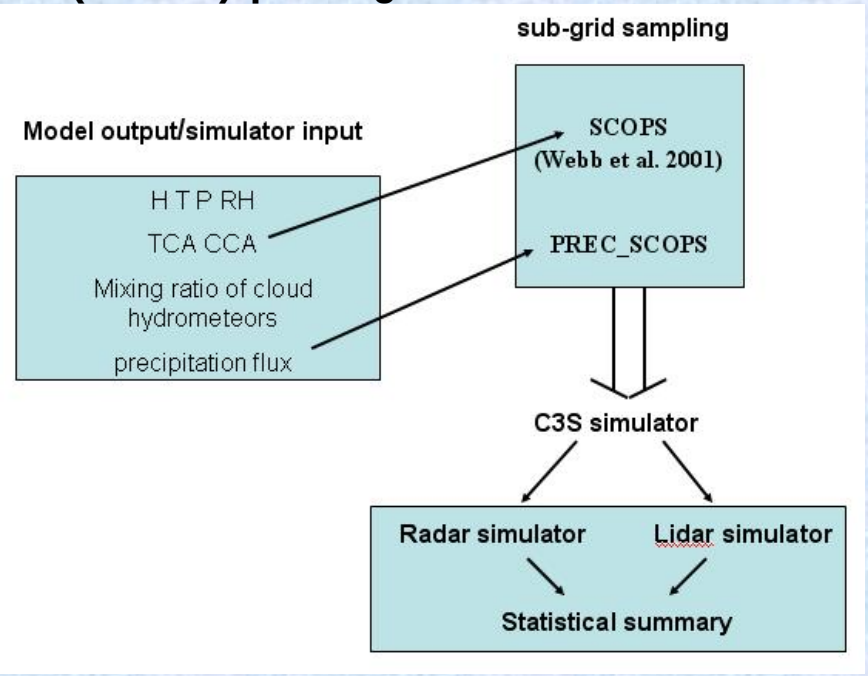
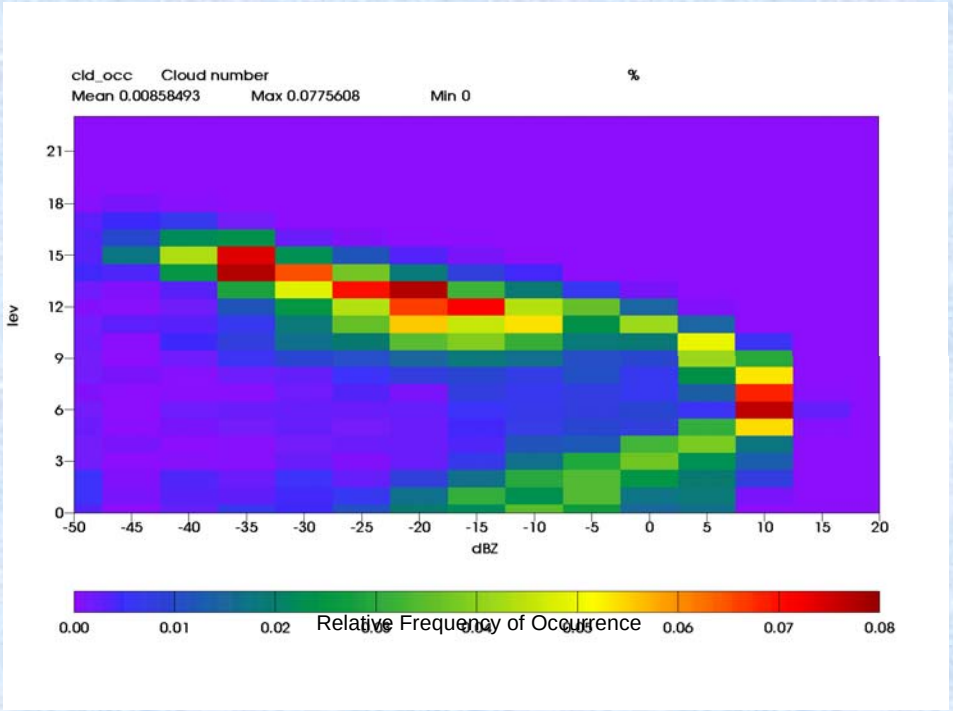
Goal: evaluate GCM simulations using combined radar and lidar data

Schematic of the CFMIP ISCCP/CloudSat/ CALIPSO simulator (CICCS) package



A sample: apply the radar simulator to the NCAR's CAM3 simulations



- **Development of CICCS is in collaboration with the Hadley Center and LMD (France), CSU, and UW**
- **Embed the CICCS in GCMs and produce the output similar to the observations**
- **Assess model performance using clustering analysis**

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Beyond the mean climate . . .

- Variability also important simulating climate change
- Extensive diagnostic approaches exist
- Development of variability metrics in its infancy

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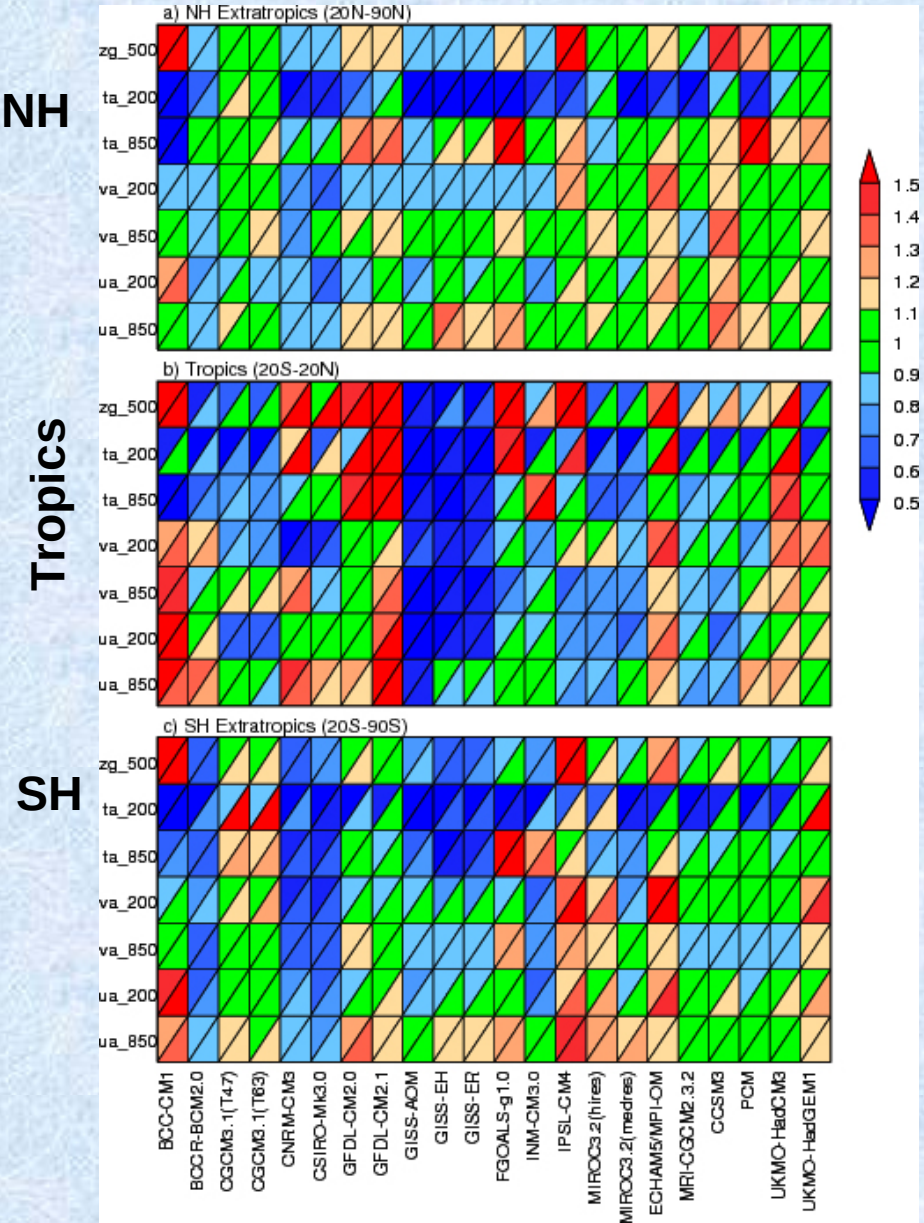
Monthly anomalies: Variance (model/reference)

- **Model anomaly amplitudes (domain average) relative to ERA40 and NCEP reanalysis (1980-1999):**

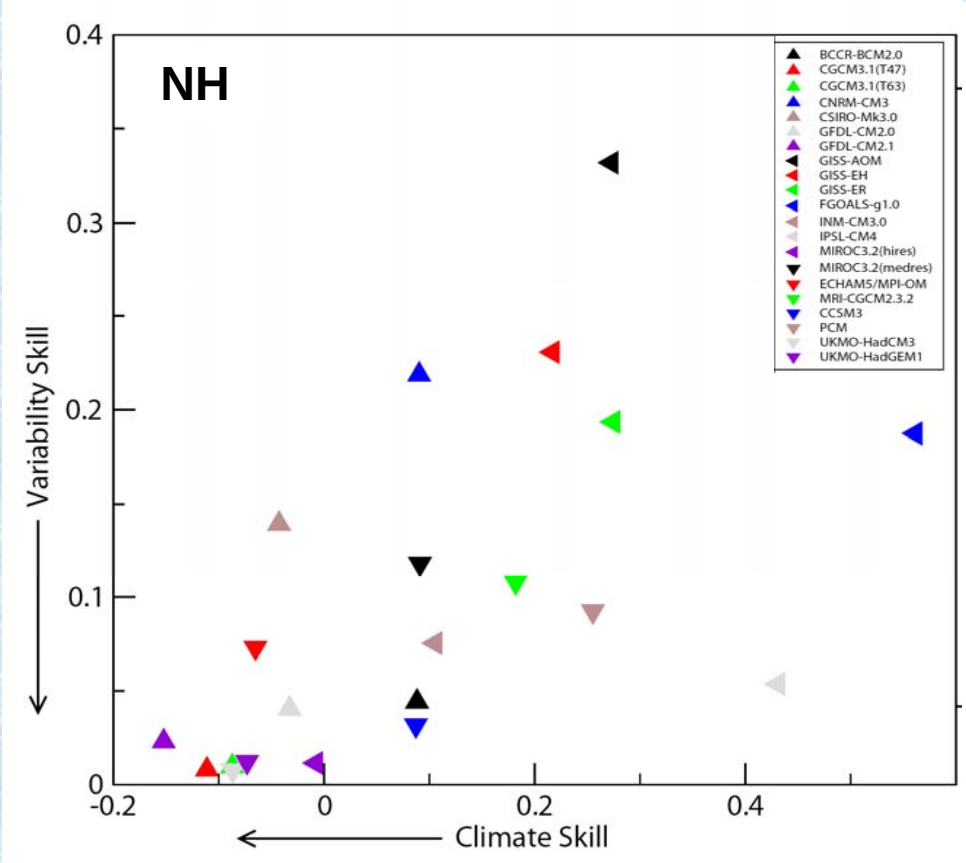
$$\frac{\text{Variance (model)}}{\text{Variance (reference)}}$$

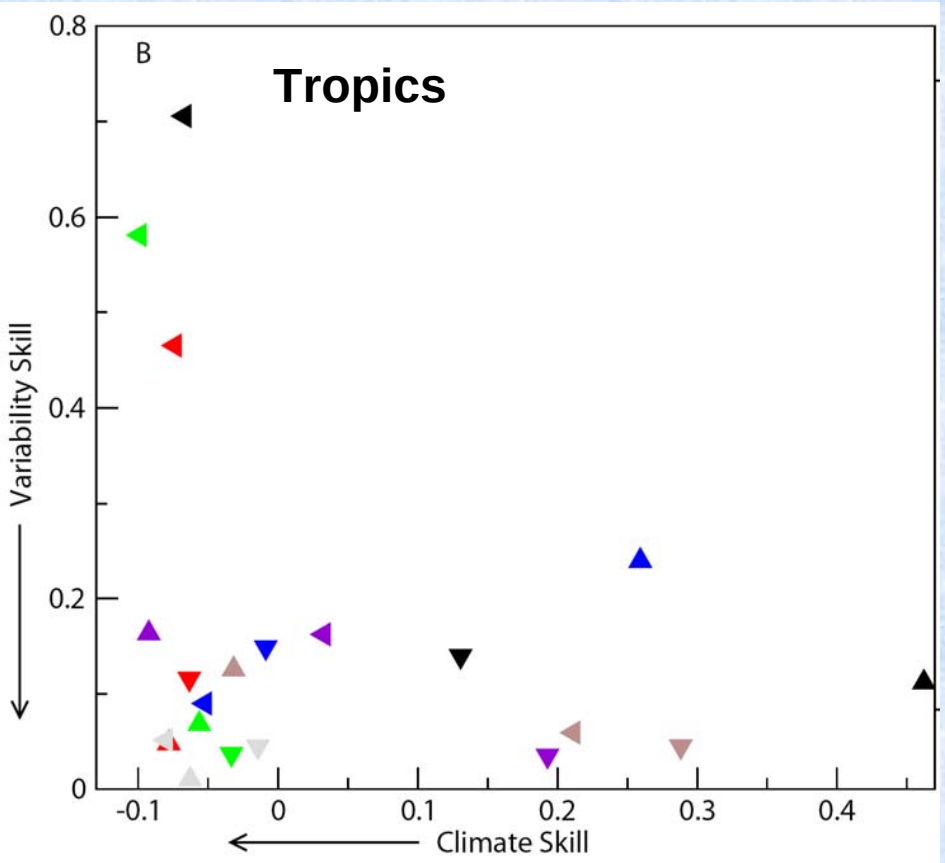
A "Model Variability Index":

$$MVI_{mr} = \sum_{f=1}^{F} \left[\beta_{mrf} - \frac{1}{\beta_{mrf}} \right]^2$$

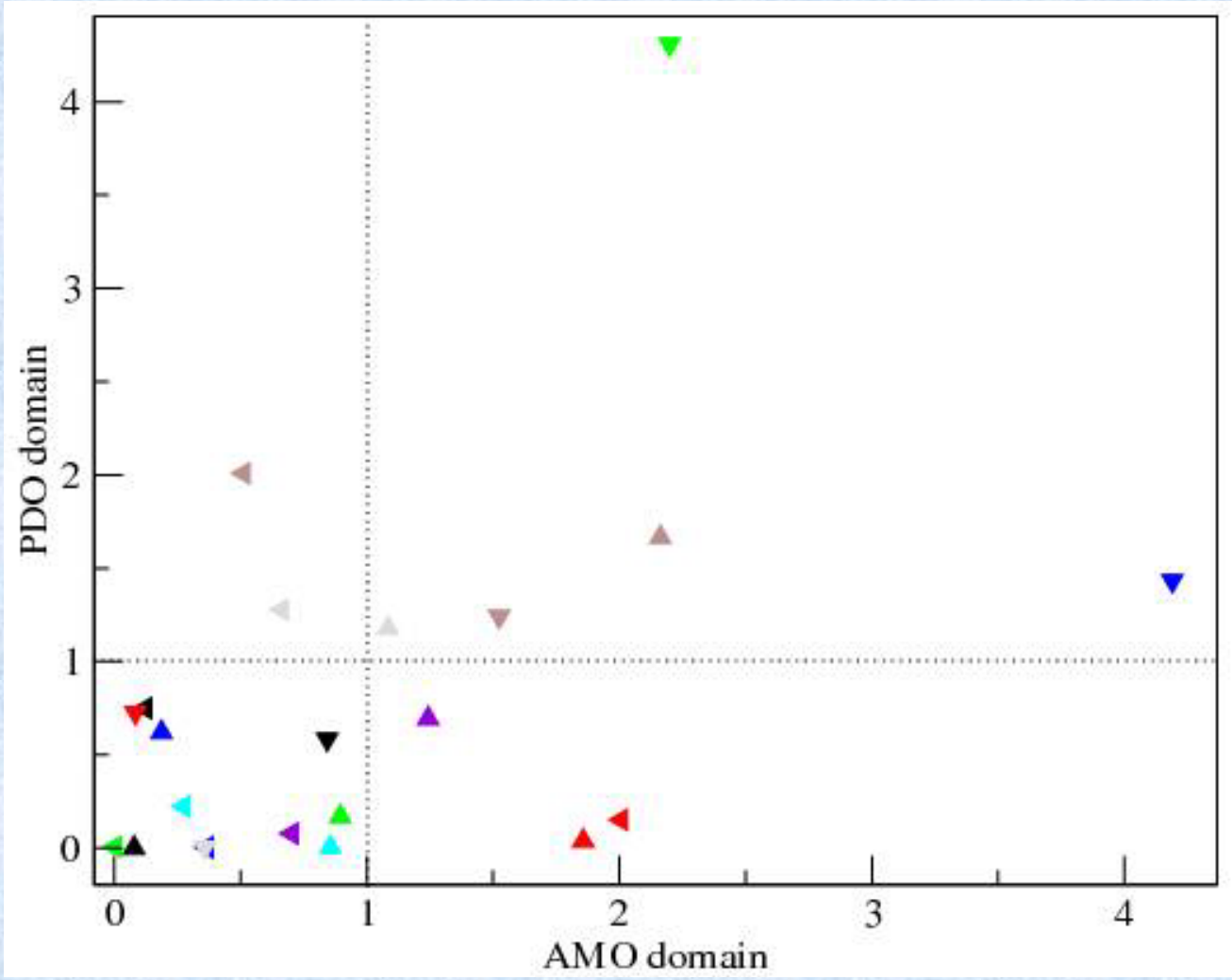


Model Skill: Mean climate vs. variability





SST anomalies: PDO vs AMO domains



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Some conclusions: performance metrics gauging relative skill

- Mean climate and variability relative skill is regionally dependent
- Weak relationship between skill in simulating mean climate and variability
- Premature to unduly emphasize a single performance index - fails to capture the complex error structure of models
- Optimal weighting of different metrics contributing to a performance index likely depends on the application
- For the moment, ruling out models based on minimal requirements seems most justifiable

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How have metrics helped us to date ?

- Force us to be more quantitative in our evaluation of models
- Enable us to track changes in model performance
- Help summarize the relative merits of different models
- Provide considerable evidence for the general superiority of the multi-model “mean simulation”

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Looking ahead:

- Community working to develop a “basket” of metrics spanning a wide range of simulated processes and phenomenon
- Establish a minimum set of routine performance metrics, minimizing redundancy
- Explore relationships between skill in simulating present climate future projections
- Work towards scientifically justifiable strategies of weighting model results of future projections
- The more state-of-the-art observations to be incorporated into this work the better…

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